2024 The 17th Workshop on Nondestructive Quality

Evaluation of Agricultural, Livestock and Fishery Products

AI-Powered Imaging and Spectral Techniques:

From Crop Growth Monitoring to Flavor Analysis

Shih-Fang Chen

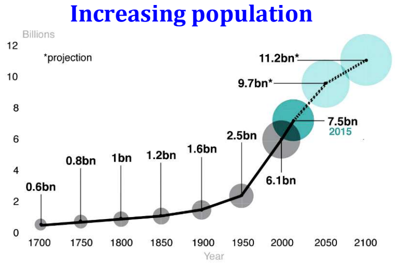
Department of Biomechatronics Engineering

National Taiwan University

Sensing and Spectroscopy Lab

Trends and Challenges in Agriculture

Increasing population



Climate changes

Limited resources and sustainability

Lack of work force

Source: https://www.nourishthefuture.org/relevant-science/growing-population-food-security

Precision/ Smart/ Digital Agriculture

Information and communication technology, IoT, big data, smart machine

Application Layer Analyze the return data from the transport layer and provide a reaction		Brain
Transport Layer Transmits data from multiple devices to an on-premise or cloud data center		Neuron system
Perception Layer Get the biological and environmental data, similar to how humans perceive it, such as temperature, pests and diseases, etc.	Sensing technology: Biology, Environment Recognition technology: Image recongnition, RFID, GPS, etc.	Senses: Touch, Sight, Taste, Smell, Hearing
Physical Layer The mechanical devices, tools, environments, and creatures used in the agriculture processing	Farmland, Agriculture, Machinery	Body

Source: Council of Agriculture, Executive Yuan, Taiwan. 2022.

Applications of Machine Vision in Agriculture

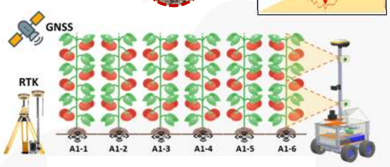
From Farm…

Image Processing

Production

Plant Growth Monitoring/Phenotyping

Pest/Disease Identification | Plant Management | Harvest Time Prediction



Tea, asparagus, tomato, cucumber, melon, vegetables, etc.

Harvest/Post-harvest

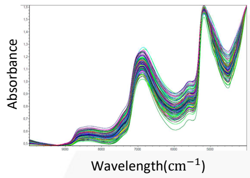
Tea Bud Identification, Tea Leaves Grading System

Applications of Spectroscopic Techs in Agriculture

From Farm…
Spectroscopic Techs

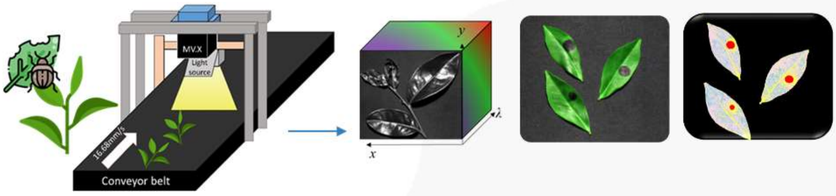
- Quality (Fishery)

Identifying Yellow and Spoiled Flesh in Taiwan Tilapia using NIR



- Quality (Plants)

Early Disease Identification by Applying Hyperspectral Images

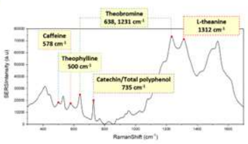


Applications of Spectroscopic Techs in Agriculture

To Market
Spectroscopic Techs

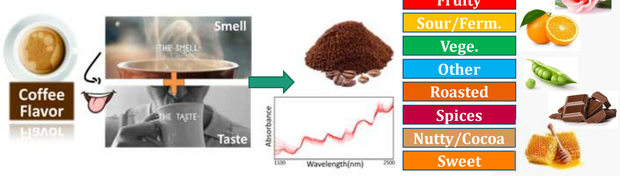
- Safety

Origin Discrimination of Tea / Pesticide Residue Detection of Herbs

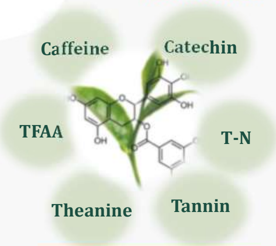


- Quality

Coffee Flavor Prediction

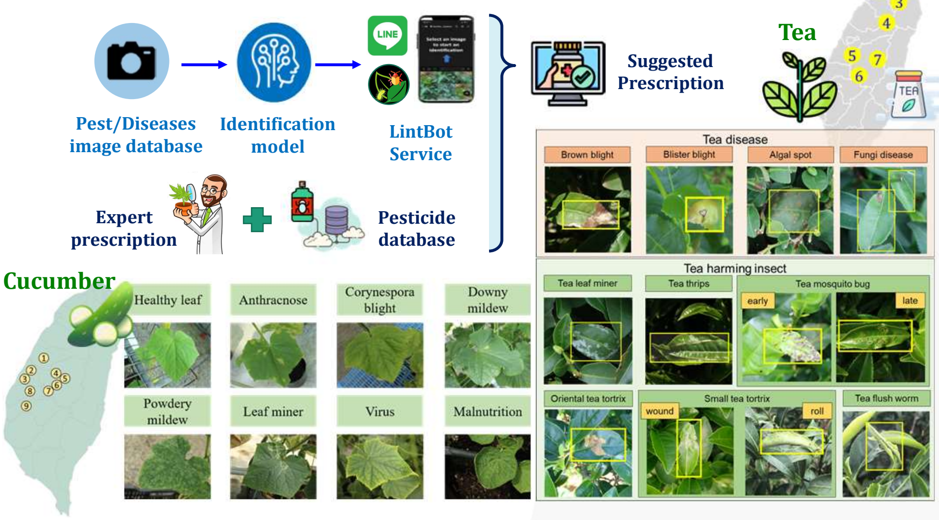


Determination of Tea Ingredient



Production Stage

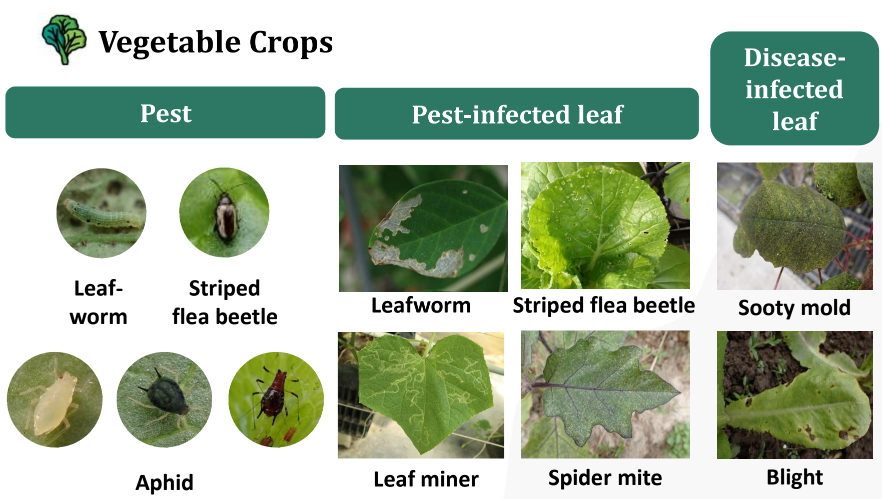
Plant Disease Identification System + Smart Prescription System



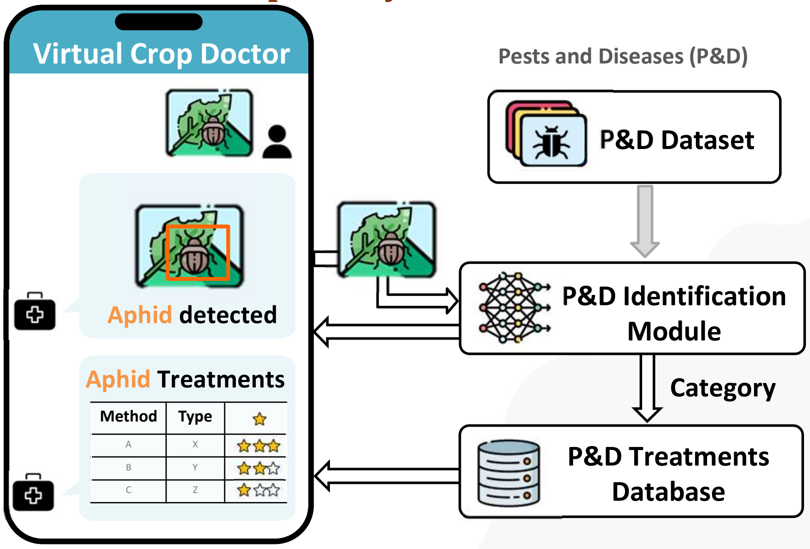
Production Stage

Plant Disease Identification System + Smart Prescription System

Vegetable Crops

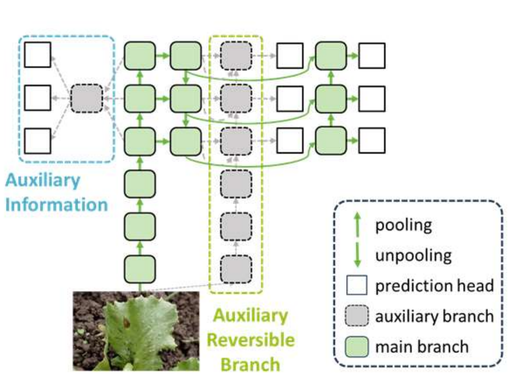


Plant Disease Identification System +
Smart Prescription System

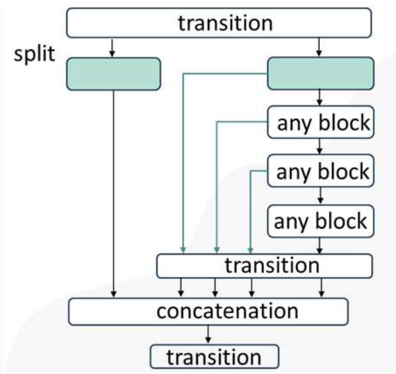


Plant Disease Identification System +
Smart Prescription System

You Only Look Once (YOLO) series: YOLOv9



Programmable Gradient Information (PGI) of YOLOv9

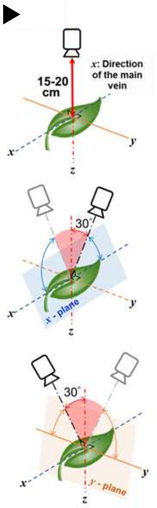


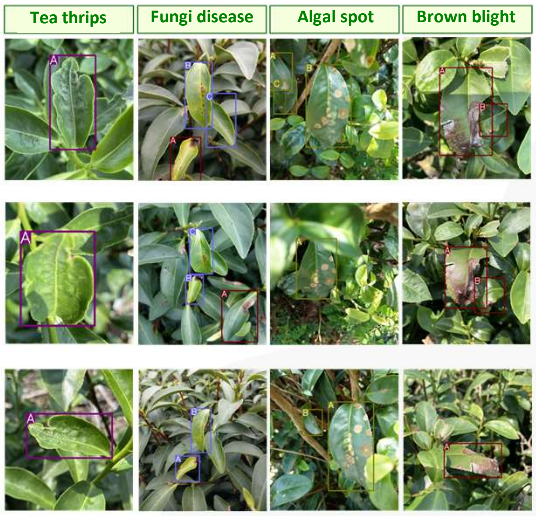
Generalized Efficient Later Aggregation Network (GELAN) in YOLOv9

Production Stage

Plant Disease Identification System +
Smart Prescription System

Collect photos ▶ from various angles and conditions





Production Stage

Plant Disease Identification System +
Smart Prescription System

LineBot Service – 'Tea Pest ID'

Upload image through LINE App

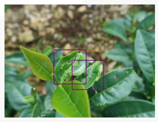
Link to Server for Identification

Display the Result: location and class

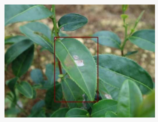
Follow-up Suggestion: link to the web "**Intelligent Prescription System**"

▲ System demonstration to farmers

▼ Thrips

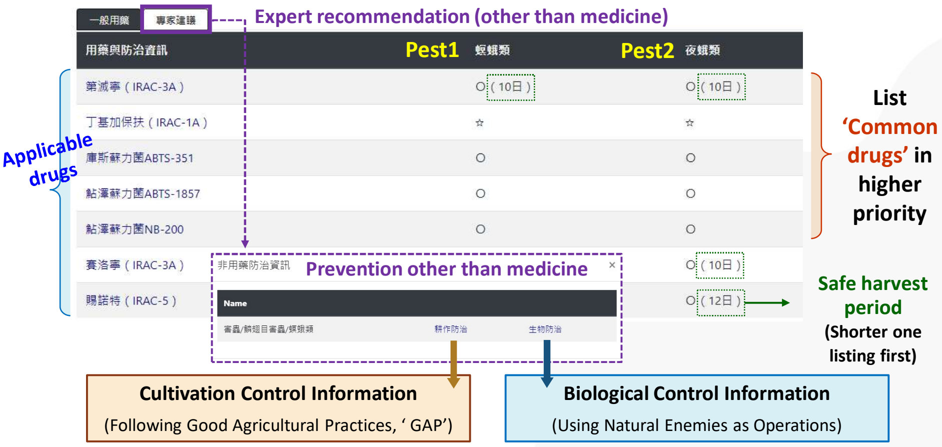


▼ Brown blight



Plant Disease Identification System + Smart Prescription System

▼ **Precision medication → lower the cost, reduce environmental impact, and increase product safety**



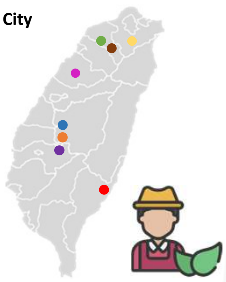
Plant Disease Identification System + Smart Prescription System

▼ **Current status of system promotion**

Tea Farmers and Plant Doctors from **different regions** participate in system validation and provide feedback periodically (**biweekly/monthly**).

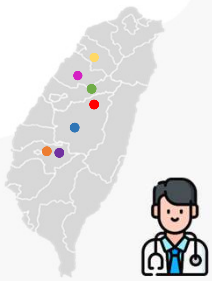
Tea Farmers

- New Taipei City
- Taoyuan 1
- Taoyuan 2
- Miaoli
- Nantou 1
- Nantou 2
- Chiayi
- Taitung



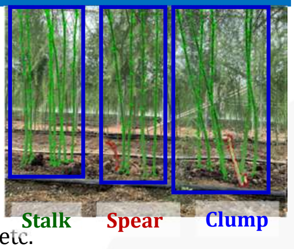
Plant Doctors

- Hsinchu
- Miaoli
- Taichung
- Nantou 1
- Nantou 2
- Chiayi 1
- Chiayi 2



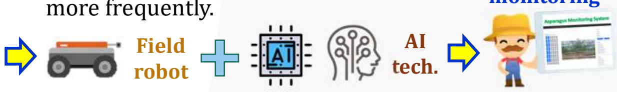
Intelligent Monitoring System for Greenhouse Asparagus Production

Temperate zone	Subtropical zone



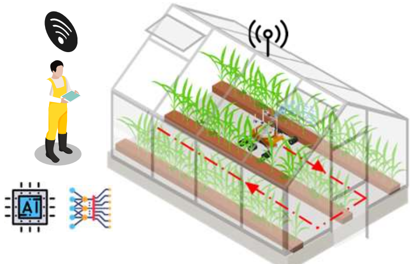
Region: mostly in US, Germany, Australia, etc.
Method: remove all stalks and leave spears only.
→ Easier for field maintenance and harvest mechanization.

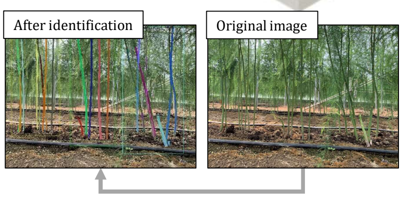
Region: Taiwan, China, Japan, etc.
Method ('**Mother Stalk Cultivation**'): keep proper amount of stalks to increase photosynthesis and help the growth of spears.
→ More work for field maintenance.
→ Require extra labor to scout the field more frequently.



Intelligent Monitoring System for Greenhouse Asparagus Production

▼ **Self-Guiding Field Robot for growth status monitoring**





Front view: Webcam

Front-view images were used to set self-guiding strategies.

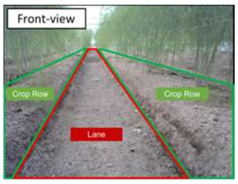
Side-view images were collected and analyzed to monitor the growth status of spears and stalks. (e.g., number and length)

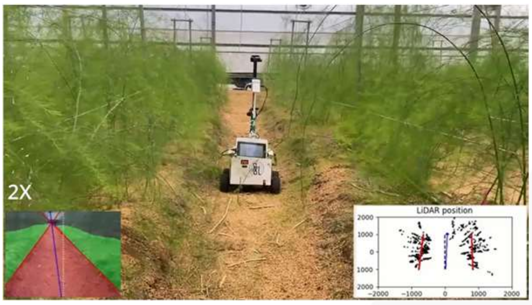
Harvest Stage

Intelligent Monitoring System for Greenhouse Asparagus Production

▼ **Self-Guiding Field Robot for growth status monitoring**

Front-view images were used to set self-guiding strategies.

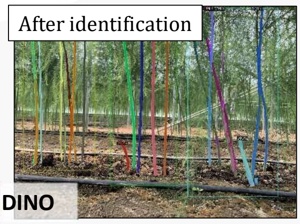




Side-view images were collected and analyzed to monitor the growth status of spears and stalks. (e.g., **number** and **length**)

Original image

After identification

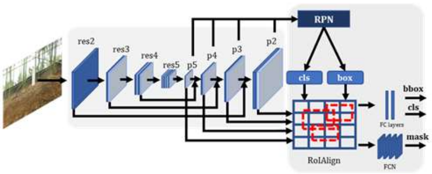


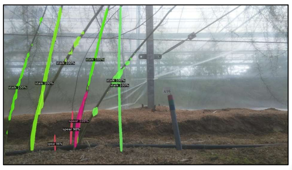
Mask DINO

Harvest Stage

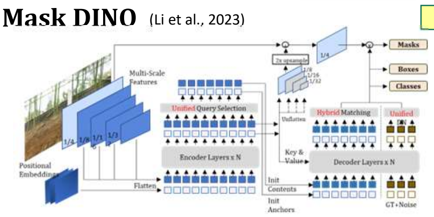
Intelligent Monitoring System for Greenhouse Asparagus Production

Mask RCNN (He et al., 2017)





Mask DINO (Li et al., 2023)



Result

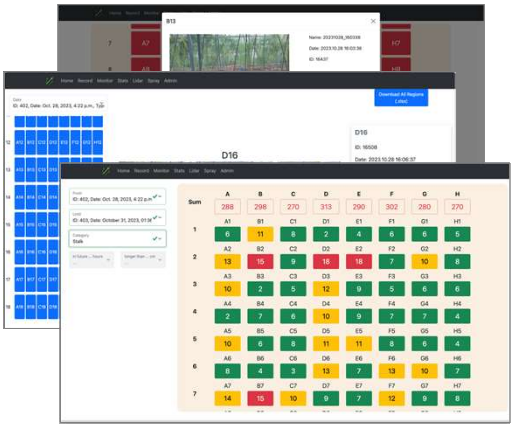
Model	Backbone	AP^{Mask}_{stalk}	AP^{Mask}_{spear}
Mask RCNN	ResNext-101	61.7	72.9
Mask DINO	ResNet-50	**95.5** ⇧	**85.2** ⇧

AP: Average Precision

Intelligent Monitoring System for Greenhouse Asparagus Production

django SQLite REST API

▼ System website



Colors: different level of density number (stalks or spears)

Record page:

The images collected by the vehicle are saved on the cloud server.
Field manager can check out the field condition remotely.

Monitor page:

Provide model identification results (e.g., category, quantity, and dimensions).

Stats page:

Provide overall stalk/spear estimation.

Intelligent Monitoring System for Greenhouse Asparagus Production

▼ Integration System for Smart Pesticide Spraying Robot

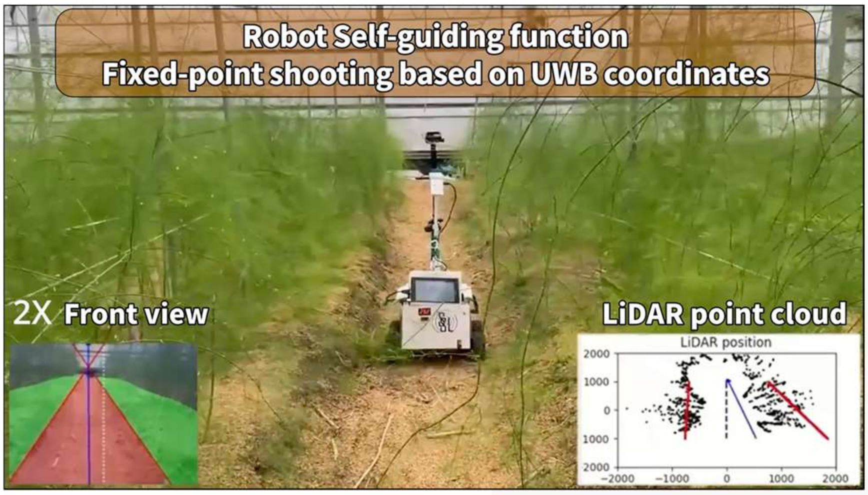
# of stalks in one meter	Density
< 15	Sparse
15~25	Medium
> 25	Dense

- Develop the smart pesticide/fertilizer robot with with Droxo Tech. (in Taiwan).
- Integrate the identification results (convert to **density level**) and location information (**UWB coordinates**) to achieve variable fertilization.

Harvest Stage

Intelligent Monitoring System for Greenhouse Asparagus Production

▼ Deminstration Video

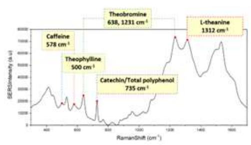


Applications of Spectroscopic Techs in Agriculture

Spectroscopic Techs

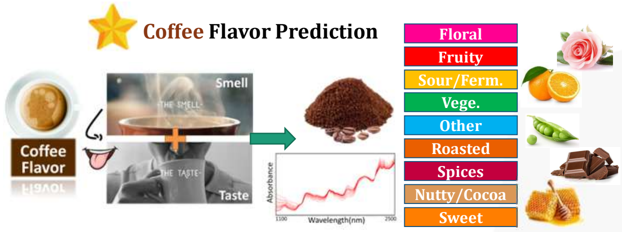
Safety

Origin Discrimination of Tea /
Pesticide Residue Detection of Herbs



Quality

Coffee Flavor Prediction



Determination of Tea Ingredient

Flavor Prediction for Specialty Coffee

▼ Apply near-infrared spectroscopy (NIR) and machine/deep learning techniques to predict potential flavor categories in specialty coffee.

Roasting degree

Origins

Processing methods

Flavor category

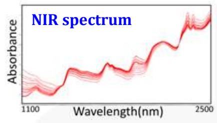
Coffee Flavor Wheel
(World Coffee Research, 2017)

Certified Cupper

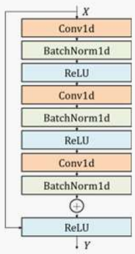
Few well-trained personnel

Chemical analysis

Time-consuming



Model structure

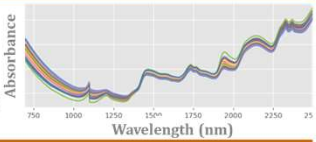


Flavor Prediction

Flavor Prediction for Specialty Coffee

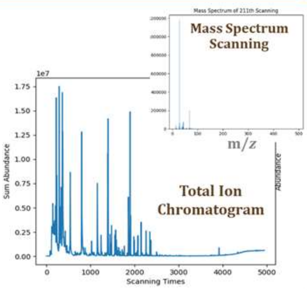
Near-Infrared Spectroscopy (NIRS)

FOSS NIRS 6500



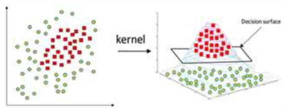
Gas Chromatography – Mass Spectrometry (GC-MS)

Agilent 7890-5975

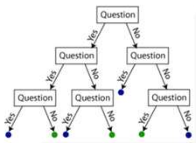


Machine Learning

SVM (Support vector machine)

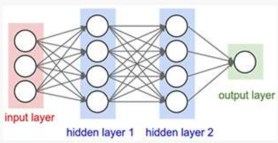


Decision tree / random forest (DT or RF)



Deep Learning

Neural network

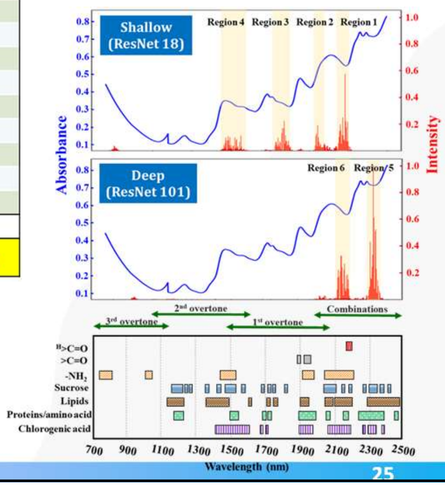


Flavor Prediction for Specialty Coffee

▼ Model Prediction

Categories	No. of Spectra	Accuracy (%)		
		SVM (RBF)	RF (entropy)	ResNet 101
Floral	85	71.59	64.77	77.27
Fruity	154	80.68	81.82	84.09
Sour/Fermented	16	92.05	93.18	92.05
Green/Vegetable	98	75	65.91	70.45
Other	72	80.68	79.55	70.45
Roasted	81	72.73	64.77	69.32
Spices	12	81.82	84.09	90.19
Nutty/Cocoa	129	82.95	70.45	79.55
Sweet	180	72.73	71.59	75
Avg(9)		78.91	75.13	78.79
Avg(7) - exclude 'sour/ferm. & spice'		76.22	71.16	75.16

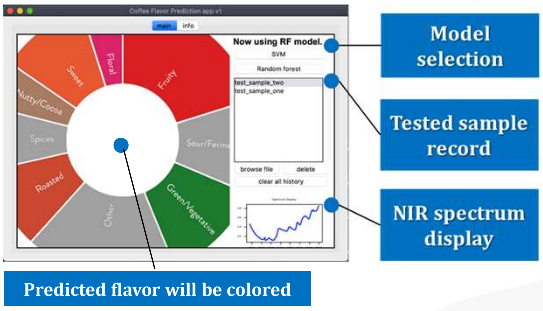
▼ Find the potential correlation between flavor categories and the corresponding chemical composition by visualizing the learned features in models.



Flavor Prediction for Specialty Coffee

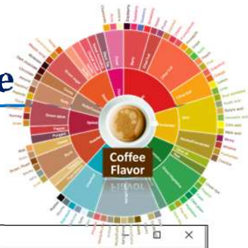
▼ Prediction Interface

Case: Ethiopia, Gesha village, Gesha, Nature, Agtron=83.8



Model	Floral	Fruity	S./F.	Veg.	Roasted	Spices	N./C.	Sweet	Other
Ens. SVM	Yes	Yes	No	Yes	No	No	Yes	Yes	No
Ens. RF	No	Yes	No	Yes	Yes	No	Yes	Yes	No
ResNet101	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Ground truth	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No

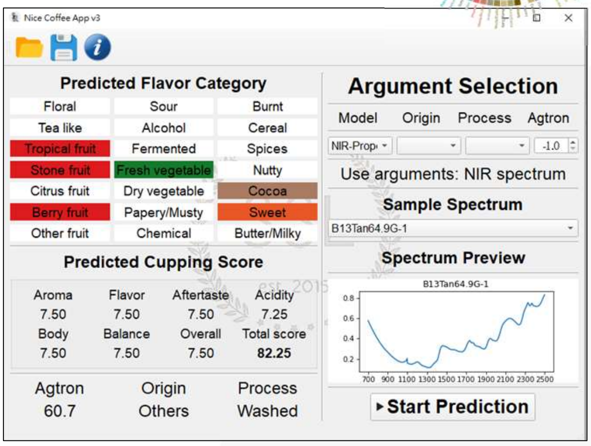
Flavor Prediction for Specialty Coffee



▼ Developing a **more versatile model** to fulfill the market demand

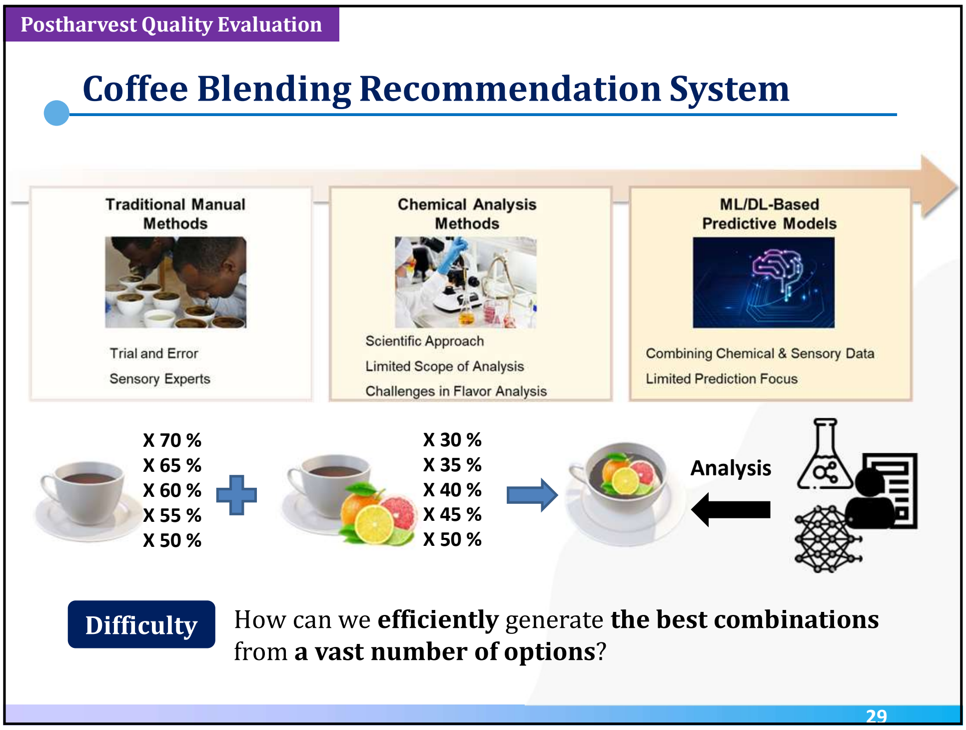
Prediction models for:

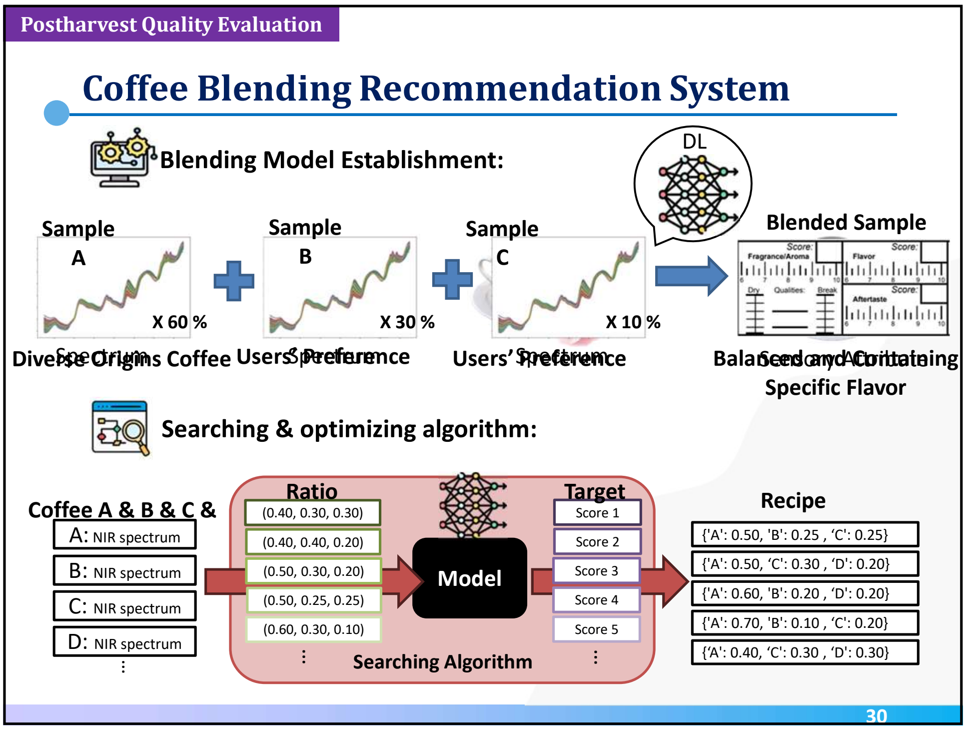
- 21 Flavors
- Cupping Score
- Roasting, origin, processing



Coffee Blending Recommendation System

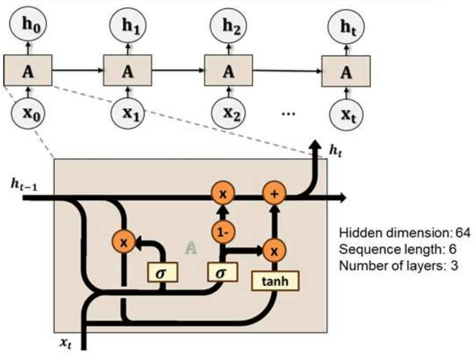
"**Coffee Blending**" is a technique commonly used in coffee production.


Postharvest Quality Evaluation
Coffee Blending Recommendation System
Traditional Manual Methods
Trial and Error
Sensory Experts
Chemical Analysis Methods
Scientific Approach
Limited Scope of Analysis
Challenges in Flavor Analysis
ML/DL-Based Predictive Models
Combining Chemical & Sensory Data
Limited Prediction Focus
X 70 %
X 65 %
X 60 %
X 55 %
X 50 %
X 30 %
X 35 %
X 40 %
X 45 %
X 50 %
Analysis
Difficulty
How can we efficiently generate the best combinations from a vast number of options?
29


Postharvest Quality Evaluation
Coffee Blending Recommendation System
Blending Model Establishment:
DL
Sample A
X 60 %
Sample B
X 30 %
Sample C
X 10 %
Spectrum
Diverse Origins Coffee
Users' Preference
Blended Sample
Balanced and Containing Specific Flavor
Searching & optimizing algorithm:
Coffee A & B & C &
A: NIR spectrum
B: NIR spectrum
C: NIR spectrum
D: NIR spectrum
Ratio
(0.40, 0.30, 0.30)
(0.40, 0.40, 0.20)
(0.50, 0.30, 0.20)
(0.50, 0.25, 0.25)
(0.60, 0.30, 0.10)
Model
Target
Score 1
Score 2
Score 3
Score 4
Score 5
Searching Algorithm
Recipe
{'A': 0.50, 'B': 0.25 , 'C': 0.25}
{'A': 0.50, 'C': 0.30 , 'D': 0.20}
{'A': 0.60, 'B': 0.20 , 'D': 0.20}
{'A': 0.70, 'B': 0.10 , 'C': 0.20}
{'A': 0.40, 'C': 0.30 , 'D': 0.30}
30

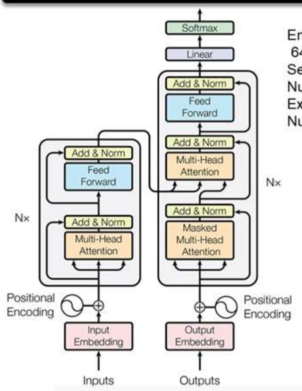
Coffee Blending Recommendation System

Model : Gate Recurrent Unit (GRU)



Hidden dimension: 64
Sequence length: 6
Number of layers: 3

Model : Transformer



Embedding dimension: 64
Sequence length: 6
Number of layers: 1
Expansion factor: 2
Number of heads: 4

Coffee Blending Recommendation System

▼ Blending Model Performance

Scoring Criterion

Mean Absolute Error (MAE)

$$\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Mean Squared Error (MSE)

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

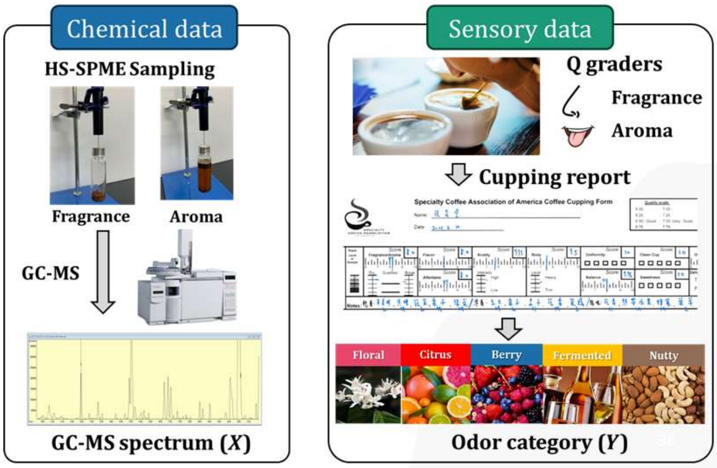
	Transformer		GRU	
	MAE	MSE	MAE	MSE
Frag./Aroma	0.113	0.027	0.123	0.029
Flavor	0.118	0.030	0.130	0.032
Aftertaste	0.122	0.032	0.137	0.032
Acidity	0.086	0.014	0.119	0.022
Body	0.100	0.016	0.121	0.029
Balance	0.121	0.027	0.157	0.038
Overall	0.119	0.025	0.156	0.035
Average	0.111	0.025	0.135	0.031

Summary:

The predictive performance of the cupping report is acceptable, with MAE for each item remaining within **0.125**.

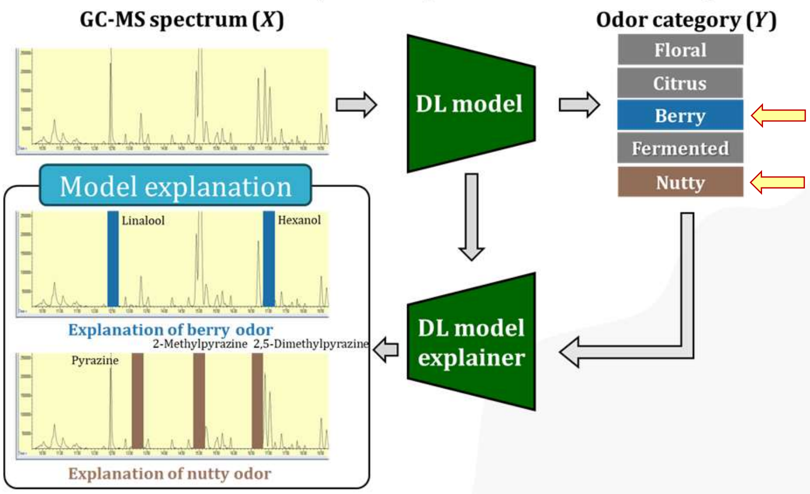
Odor Recognition for Specialty Coffee

▼ Apply **gas chromatography-mass spectrometry (GC-MS)** and deep learning techniques to predict odor categories in specialty coffee.



Odor Recognition for Specialty Coffee

How does DL model explain its prediction on GC-MS spectra?

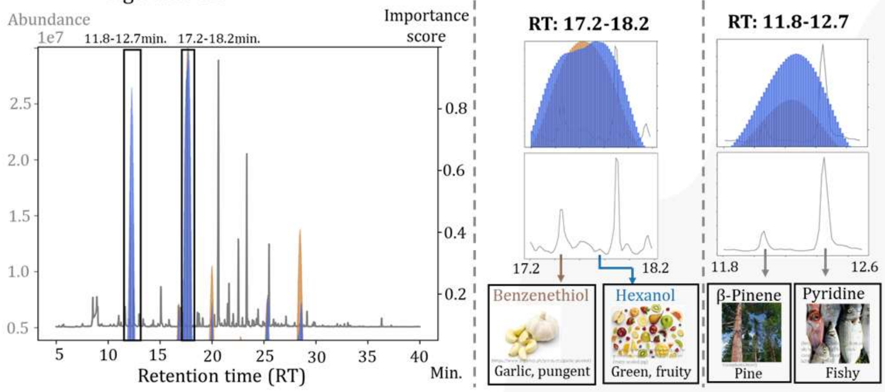


Odor Recognition for Specialty Coffee

DL model explanation (case study)

Coffee origin: Ethiopia, Gedeo, Kochere
process: washed
Agtron: 76.3

	Floral	Citrus	Berry	Fermented	Nutty
Ground truth	0	0	1	0	0
DL model	0	0	1	0	1



2024 The 17th Workshop on Nondestructive Quality

Evaluation of Agricultural, Livestock and Fishery Products

Thank you.

NSTC 國家科學及技術委員會 National Science and Technology Council

農業部 MINISTRY OF AGRICULTURE

工業技術研究院 Industrial Technology Research Institute

SSL **All the members from Sensing and Spectroscopy Lab**